A LEARNING-BASED GAIT ESTIMATION DURING WALKING-IN-PLACE IN VR LOCOMOTION SYSTEM

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This study estimated the spatiotemporal gait parameters from step time information during walking-in-place (WIP) and body anthropometric information from a newly developed VR locomotion system using a learning-based regressor. A fully-connected feed-forward neural network model was used to predict the spatiotemporal variables of walking. The inputs of the model were the WIP features and body anthropometric data, while the outputs of the model were the spatiotemporal gait parameters of the regular walking. With the prediction accuracy of 98% or higher, the feasibility of the model has been validated. In conclusion, the model not only can provide accurate prediction of spatiotemporal gait parameters while the users are walking in the VR locomotion system, but also eliminate the need to measure these parameters in experimental environments. Future studies with various subject groups such as the elderly and patients with musculoskeletal injuries will be conducted to generalize the findings of this study.

KEYWORDS: gait spatiotemporal parameters, walking-in-place, virtual reality (VR), VR locomotion system

INTRODUCTION: Quantitative gait assessment is especially important to monitor the health status and the probability of falls of the elderly, and to make a timely intervention for appropriate medical prescriptions (Mun, Choi, Chun, Hong, & Kim, 2017; Winter, 1991). Recently, smart-home environments have been established for health monitoring and smart aging, and researchers have actively contributed to the development of virtual locomotion systems to increase the elderly's willingness and amount of exercise (Feasel, Whitton, & Wendt, 2008). The navigation control of a VR locomotion system is possible through direct interaction using physical movement between the user and virtual reality system, or indirect interaction using equipment such as button or joystick. The direct interaction can increase the realism of the system and the effect of exercise by reducing the motion sickness resulting from the difference between VR environment and the actual motion intention of users. In particular, walking-in-place (WIP) is similar to actual walking and enhances the intuition of the users to control the virtual locomotion by mimicking real walking in a limited walking spot (Bruno, Pereira, & Jorge, 2013). General WIP-based locomotion systems update the gait velocity in a VR environment using subjects' height, step frequency, and vertical height amplitude of the foot during WIP (Bruno et al., 2013). However, the physical mechanisms in WIP and actual walking are slightly different. In case of WIP, the foot moves vertically by exerting the hip and knee muscles, while all lower limb muscles including ankle joint are timely contracted in the actual walking (Bruno, Sousa, Ferreira, Pereira, & Jorge, 2017). Therefore, the direct transfer of the WIP parameters into VR locomotion system may cause an unnatural translation as well as motion sickness to the users (Wendt, Whitton, & Brooks, 2010). In addition, systems which can estimate the actual walking pattern while the users are engaging with a VR locomotion system are required to quantitatively assess the gait performance, and to monitor their health status as well as exercise capacity for the elderly. The WIP parameters have been actively used for controlling VR navigation systems but not for the quantitative gait estimation system yet. Measuring human gait extensively relies on spatiotemporal characteristics of an individual such as the time and length of stride and step, stance time, swing time, single-limb support (SLS) time, double-limb support (DLS) time, and gait velocity. Therefore, the purpose of this study was to estimate the gait spatiotemporal parameters from WIP time parameters and body anthropometric information from a VR locomotion system based on a learning-based regressor.

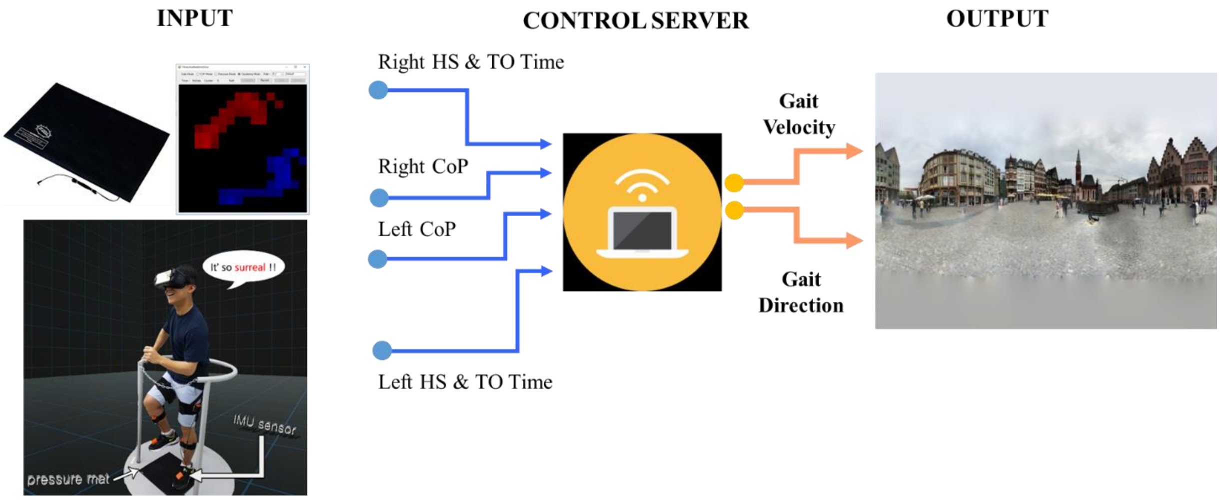

Figure 1: An overview of the VR locomotion system used in this study

METHODS: The VR locomotion system consists of a foot pressure measurement device for user interaction, a virtual reality system for visualization, and data analysis software for the locomotion control (Figure 1). As an input, the pressure measurement device is a 40 x 40 cm square mattress with 16x16 pressure sensors, and provides foot pressure and position information during WIP. As an output, the virtual reality system consists of visualization gear projecting virtual images implemented by a physical engine. As a control server, the data analysis server takes heel-strike and toe-off time as well as the center of pressure (CoP) of each foot, then calculates the gait velocity and direction. These are transmitted to the virtual reality system for the navigation.

Forty subjects participated in this experiment. The experiment consisted of a WIP session and a regular walking session. Before the sessions, all subjects' body anthropometric information such as ankle height, knee height, hip height, body height, hip width, and shoulder width were manually measured, then the commercialized IMU sensor system (Xsens MVN, Enschede, Netherland) was worn to measure the joint angles of the lower limbs. In the WIP session, all subjects were instructed to perform 30 strides of walking on the pressure sensor in the space where the safety handle was installed, and the middle 10 strides were extracted for the analysis. In the regular walking session, all subjects were asked to walk a 30m straight line at their preferred and comfortable speed, and the middle 10 strides were used for analysis.

The following features were calculated during the WIP session: 1) four step frequency information such as stride time, step time, single-limb-support (SLS) time, and double-limb support (DLS) time, 2) joint kinematic information such as maximum and minimum joint angles, and their range of motions (RoMs). The spatiotemporal gait parameters (stride time, step time, swing time, SLS time, DLS time, stride length, step length, and gait velocity) were measured in the regular walking session.

A fully-connected feed-forward neural network model consisting of two hidden layers with 'Adam' optimizer and 'ReLU' activation function was used to predict the spatiotemporal variables of walking. The number of neurons for each layer was as twice the number of input variables. The inputs of the model were the WIP features and body anthropometric data, while the outputs of the model were the spatiotemporal gait parameters of the regular walking. To find the optimal input data set, we separated the input groups into four groups: Group 1) the step frequency information; Group 2) Group 1 + body anthropometric data; Group 3) Group 2 + min/max of joint angles; Group 4) Group 3 + RoMs of the joint angles. The mean-square-error (MSE) was calculated to evaluate model performance.

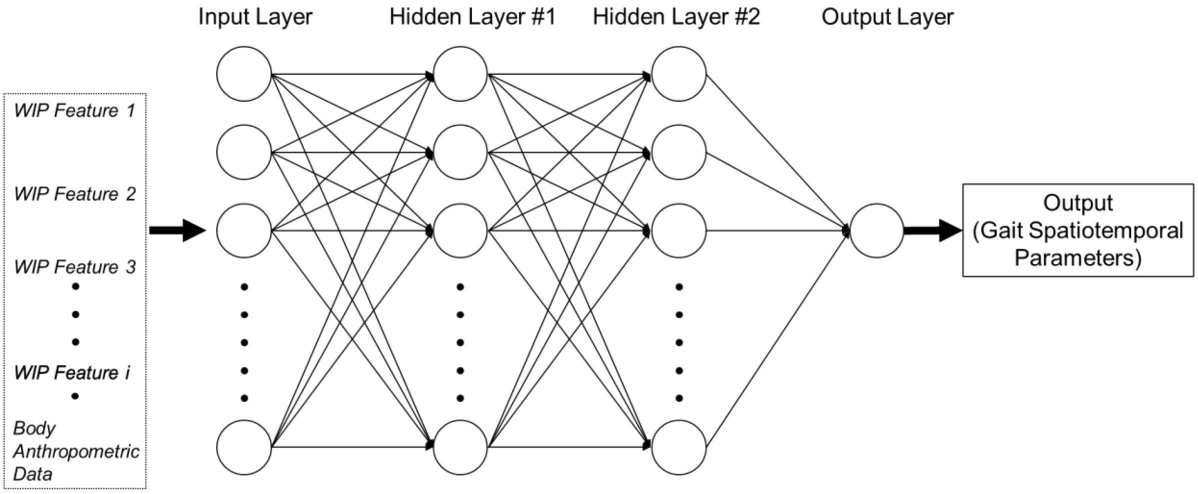

Figure 2: A developed learning-based regressor to estimate spatiotemporal gait parameters using WIP features and body anthropometric data

RESULTS: The MSEs and SDs of gait spatiotemporal parameters at the preferred speed are shown in Figure 3. The prediction accuracies are summarized in Table 1. The estimation accuracy of spatiotemporal gait parameters increased as the number of inputs increased. The minimum accuracy in the gait temporal parameters was 98.16 % at DLS time in group 1, while the maximum accuracy was 99.85 at swing time in group 3. The accuracy in the gait temporal parameters was the highest in group 4 while the lowest in group 1. However, there was no remarkable difference according to the group compositions. The MSEs and SDs in the gait spatial parameters in group 1 were relatively higher than the other groups. Especially, the accuracy of gait velocity estimation in group 1 was 94.79% while the other groups showed above 98%.

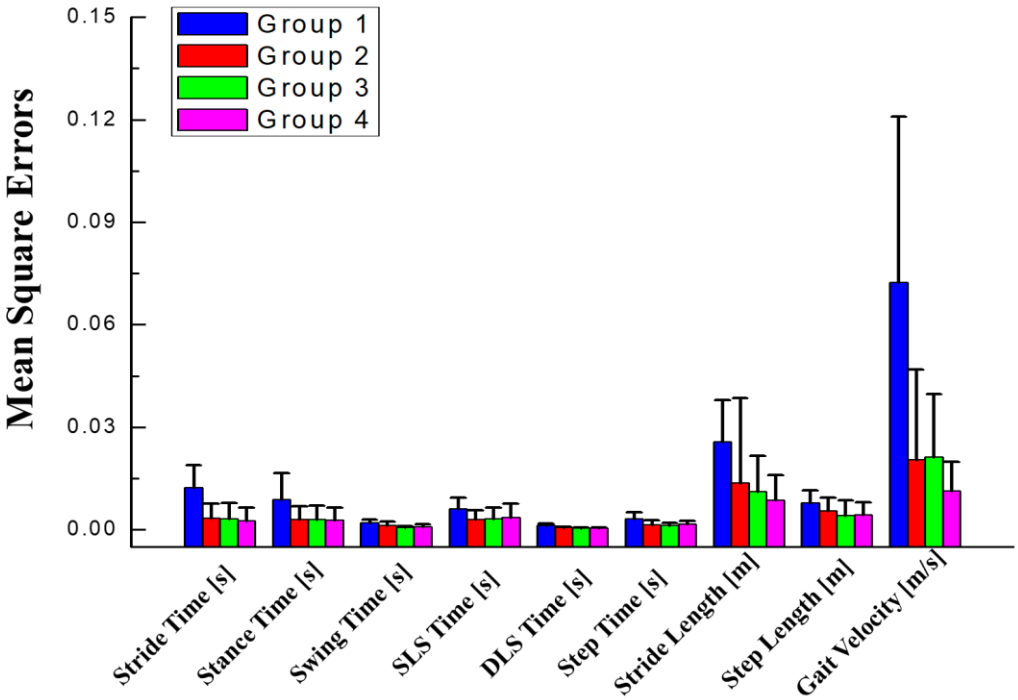

Figure 3: Mean square errors and standard deviations between actual gait parameters and estimated gait parameters

Table 1: Estimation accuracy according to the different group compositions

	Stride Time [s]	Stance Time [s]	Swing Time [s]	SLS Time [s]	DLS Time [s]	Step Time [s]	Stride Length [m]	Step Length [m]	Gait Velocity [m/s]
Group1	98.86	98.54	99.56	98.88	98.16	99.39	98.25	98.94	94.79
Group2	99.68	99.49	99.73	99.43	99.03	99.74	99.08	99.24	98.53
Group3	99.70	99.49	99.85	99.39	99.33	99.77	99.24	99.43	98.47
Group4	99.76	99.55	99.81	99.34	99.28	99.71	99.42	99.40	99.19

DISCUSSION: We developed a system that can walk freely in VR system during WIP. This study not only overcame the constraints of the existing gait navigation system but also improved the responsiveness, as well as updated the user's intention and speed in real-time, contributing to the reduction of the gap between WIP and actual walking. Using this VR locomotion system, the study estimates the total 9 gait outcomes including stride time, stance time, swing time, SLS time, DLS time, step time, stride length, step length, and gait velocity in preferred walking speed using WIP parameters and body anthropometric data while subjects are walking in the VR locomotion system. Although the MSEs were the highest in group 1 on the gait temporal parameters, the accuracies are above 98% showing the feasibility of the gait estimation by only using the WIP time parameters. In other words, the gait temporal parameters were successfully estimated by only using WIP temporal parameters in group 1. However, the MSEs and SDs were remarkably high and the accuracies were lower in group 1 for the gait spatial parameter estimation compared to the other groups. It seems that the WIP step frequency information are not enough to estimate gait spatial parameters such as stride and step length, and the gait velocity since this information are more related to the body size information as well as joint kinematics during WIP. For the most of the output variables, there was no considerable difference found between group 2 and group 3, and between group 2 and group 4. Thus, it can be concluded that the input variables in group 2 are the most optimized and effective input set for the gait spatiotemporal estimation since the group 2 only require the VR locomotion system with subject's body anthropometric data, not additional IMU sensors attached on the body to measure the kinematic information.

CONCLUSION: This study developed a learning-based regressor that estimates spatiotemporal gait parameters using the step frequency information during WIP and body anthropometric data. The model not only can provide accurate spatiotemporal gait parameters while the users are walking in the VR locomotion system, but also eliminate need to measure these parameters in the experimental environments. Future studies with various subject-groups such as the elderly and patients with musculoskeletal injuries will be conducted to generalize the findings of this study.

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